Total Variation Electrocardiogram Filtering

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Abstract

We examine the performance of Total Variation (TV) smoothing for processing of noisy Electrocardiogram (ECG) recorded by an ambulatory device. The TV smoothing is compared with traditionally-used band-pass filtering using ECG with artificially added noise, as well as with real-world noise obtained during physiological monitoring. The fundamental difference between TV smoothing and traditional band-pass filtering is that TV smoothing allow preserving sharp slopes in the ECG, while traditional smoothing dampens them. Since the QRS complex represents a feature with steep slopes, the TV smoothing is a better choice ECG filtering. We found that TV smoothing outperforms traditional filtering on ECG signals recorded under different conditions and can be used as effective filtering tool in popular QRS detection algorithms.

Introduction

Modern ambulatory physiologic monitoring devices are capable of collecting a large number of vital signs with high sampling rates. However, such data, obtained in the field, contain significant amount of noise mostly due to movement artifacts. One of the most important vital signs collected by practically all wearable physiologic monitoring systems is heart rate, derived from ECG waveform. The problem of ECG filtering has been a subject of numerous studies and has been tackled with a wide range of signal processing techniques which vary from linear bandpass filtering to neural networks (Arzeno et al. 2008, Friesen et al. 1990, Hamilton, and Tompkins, 1986). The linear bandpass filtering is, however, the most widely used technique due to its simplicity, efficiency, and speed. Nevertheless, it is not without faults. The shortcomings of the linear band pass filtering comes from its very nature of being a smoothing technique. As a smoothing technique, the bandpass filter does not preserve ECG features with the highest rate of change or the steepest slope. Ironically, the QRS complex is the feature with the highest rate of change and hence part of its energy is filtered out by a bandpass filter.

Total Variation Smoothing

Recently, some slope-preserving methods were put forward, mostly for image processing tasks (Rudin et al. 1992, Hansen 2010). The most prominent slope-preserving smoothing technique is Total Variation (TV) smoothing which seeks to minimize the following functional (Rudin et al. 1992):

$$E = \|y - f(x)\|^2 + \alpha\,|Df(x)| \qquad (1)$$

where y is the measured noisy ECG waveform, f(x) – filtered ECG, D is the first-order derivative operator, and α is the regularization parameter. Notice that equation (1) uses two different norms in its first and second terms. The first term uses the Euclidean least squares norm and the second one uses the Manhattan norm of the first derivative of the filtered waveform. It is this second term which gives the TV smoothing its slope-preserving properties.

The second term in equation (1) is measuring function's total variation, which is usually defined as:

$$S_{TV}\left(f(x)\right) = \int_0^1 |f'(x)|dx \qquad (2)$$

The main advantage of using the TV smoothing is that it penalizes the nonsmoothness of the solution in quite different manner than traditional smoothing techniques. Specifically, the TV penalty does not depend on the steepness of the slope, thus allowing sharp edges into the filtered signal. On the other hand, the TV smoothing is still a low pass filter, which effectively filters out high-frequency noise.

Results

We compared the performance of the TV filtering with a commonly used Butterworth bandpass filter with the pass band between 5 and 15 Hz. Figure 1 shows an example of applying TV and Butterworth filtering to a triangular impulse contaminated with noise.

As can be seen in Fig.1, the Butterworth filter significantly attenuated the peak of the impulse and also introduced sidelobe artifacts, which are not present in the original signal. These undesirable effects can significantly complicated peak detection and leak to missed or spurious peaks.

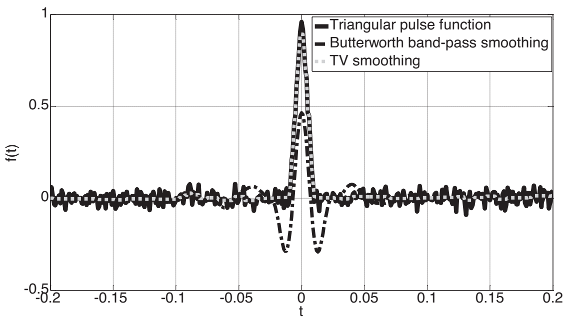

Figure 1 Comparison of TV and Butterworth filtering for a triangular impulse

In contrast, the TV filtering preserved most of the peak's energy and also showed no sidelobe artifacts, thus leading to a filtered signal with better signal-to-noise-ratio.

The same observation can be made while using the TV smoothing for a real ECG recoding. Figure 2 shows a small portion of an ECG recording obtained in ambulatory conditions using Equivital physiologic monitoring system (Hidalgo Limited, UK). The monitor is an FDA-approved complete human physiological monitoring platform, allowing measurements of human physiology in both laboratory based and field research. The chest worn ambulatory monitor device provides real time measurements of core temperature, skin temperature, heart rate, respiratory rate, and physical activity. On these data, as well, the TV smoothing demonstrates its superior edge-preserving properties in comparison with Butterworth filtering.

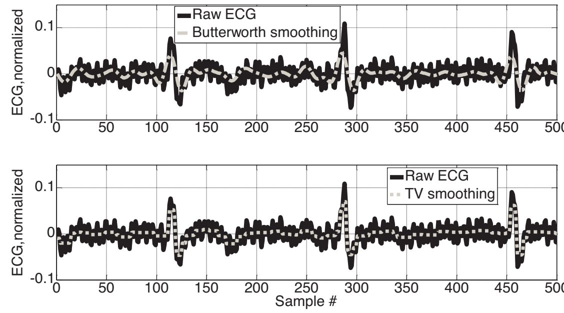

Figure 2 Application of Butterworth band-pass filtering (top panel) and TV (bottom panel) smoothing to a real ECG signal.

However, the ECG filtering is usually only the initial step in the ECG processing, which is aimed at QRS detection and beat time identification.

To validate the TV smoothing, we modified and customized a well-known algorithm (Pan, and Tompkins 1985) to fit the needs of our perspective applications. In the first stage, the algorithm uses a 5- to 15-Hz Butterworth band-pass filter to eliminate non-QRS-related frequencies, and in the second stage, it computes the difference between two consecutive points to amplify the sharp slopes of the QRS complex. After differencing, it squared the resulting signal to make the ECG samples positive and to amplify the high-frequency components. Finally, in the last stage, it uses a low-pass filter to enhance the fiducial marks of the QRS complex and implements a self-adaptive thresholding method to detect QRS peaks, reject noise, discriminate T-waves, and search back for missed QRS complexes if a detection was not made within a certain time interval

Our modification concerned only the first stage of the algorithm, namely, we replaced the Butterworth filter with TV smoothing leaving the rest of the algorithm unchanged. Consequently, we compared the performance of the original algorithm with the one that uses the TV smoothing. The comparison was performed on the ECG waveform collected during the study on glycemic control in young adults performed at the USDA Beltsville Human Nutrition Center. The study has been approved by the IRBs of all participating institutions. The first set of tests consisted in selecting a very clean ECG segments and their subsequent contamination with Gaussian white noise of different intensities. By adding Gaussian noise with different standard deviations, different signal-to-noise (S/N) ratios have been simulated. A total number of 100 one-minute long ECG segments have been selected and, after adding Gaussian noise, was processes by the previously described QRS-detection algorithm. The performance of the algorithms implementing TV smoothing and

Butterworth filtering has been compared in terms of Root Mean Squared Error (RMSE) between the instantaneous heart rates (HR) obtained from noise-contaminated ECG and original clean ECG. The RMSE was defined as the square root of the mean squared difference between the estimated and the ground-truth HRs after both HRs had been resampled to 1 Hz via linear interpolation. The average RMSE for 100 segments was estimated and the results for four different S/N ratios are summarized in Table 1.

As can be seen from Table 1, the TV smoothing consistently outperform the Butterworth filtering in terms of RMSE.

S/N	10	5	3	1	Real World
RMSE, bpm, Butterworth	0.20	0.25	0.29	44.30	2.12
RMSE, bpm TV	0.15	0.20	0.21	17.30	0.51

Table 1 Comparison of Butterworth filtering and TV smoothing for different signal-to-noise ratios and for the real-world noise contamination.

The second test was performed using the real-world noise found in the ECG recordings. The Hidalgo system uses a two channel ECG recording for redundancy and more reliable measurements. In some ECG segments, one ECG channel was found to be noise-contaminated, while the other one was noise free, as demonstrated in Fig. 3. We selected 100 such segments and used the noise-free channel to calculate the ground truth heart rate while the noisy channel was used to test the algorithms.

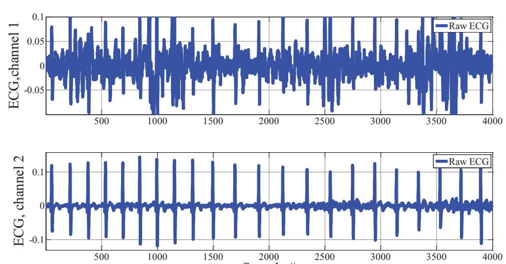

Figure 3 An example of two-channel ECG segment with channel one (top panel) contaminated with noise and channel two (bottom panel), noise free. Such segments were used to compare two algorithms in the presence of real-world noise.

The average RMSE for the 100 segments was calculated and the results are presented in the last column of Table 1. As we can see, the RMSE obtained using the TV smoothing is more than four time smaller than the corresponding band-pass filter RMSE.

Discussion and Conclusions

The TV smoothing provides a powerful edge-preserving smoothing technique, which compares favorably with tradition band-pass filtering used in ECG preprocessing. The TV smoothing consistently outperformed the Butterworth band-pass filter in our test using artificially-generated, as well as, real world noise. The power of TV smoothing comes from its ability to preserve sharp gradients in the signal, thus allowing for the QRS complexes to pass through filtering process relatively undistorted. The frequency response of the Butterwoth filter and TV smoothing is shown in Fig. 4. Notice, while the TV smoothing performs as a band-pass filter, it preserves more high-frequency information, which is evident form the fact that the solid black line is higher in every frequency range. The TV smoothing has only one parameter to select: α in (1). This parameter is equivalent to selection of the pass band for the liner filter. The higher the parameter, the more high-frequency information is removed from the filtered signal. In this study, we used the discrepancy principle (Morozov, 1993) to select the parameter, since the noise level in the ECG could be reasonably-well estimated. Also, in contrast to other edge-preserving filtering techniques, the TV smoothing does not require the knowledge of edge locations, which can be impossible to determine in real-life applications. Similar to linear filtering, the TV smoothing has Bayesian interpretation, it assumes that the sought solution has Laplace distribution, in contrast to traditional filtering, which assumes Gaussian distribution.

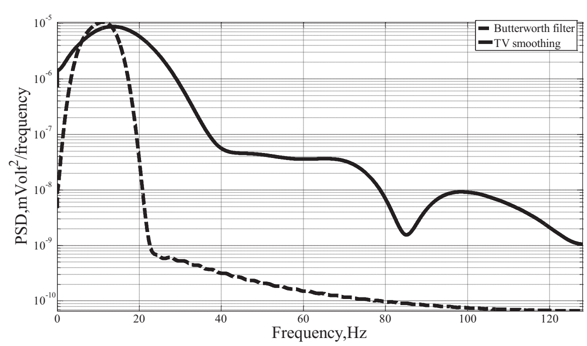

Fig. 4 Frequency response of TV smoothing (solid) and Butterworth filter (dashed).

One of the disadvantages of the TV smoothing is that there is no closed-form solution to minimize (1).

However, the recent advances in the numerical implementation of TV algorithms made them computationally competitive with traditional liner filters. In this work we used the TV algorithm described in (Little, Jones 2010).

Disclaimer

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